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# Assessing English Teaching and Evaluation Methods based on Neural Networks

**Wen Zhang**
Xinxiang Vocational and Technical College
Xinxiang, Henan, 453006, China
zhangwenxxvtc@163.com

**ABSTRACT**

*Neurolinguistics has been widely recognized for its focus on exploring the formation mechanisms of human language and its potentially significant impact on language expressivity. This article introduces an evaluation mechanism based on the BP neural network. It can help us better evaluate teaching effectiveness and potentially significantly influence teaching outcomes. We aim to enhance teaching efficacy and assist learners in improving their learning outcomes. Using MATLAB to assess the teaching efficiency of English classes, we found this approach eliminates the subjective influence of professionals and yields satisfactory conclusions applicable in various circumstances.*

**Keywords**: BP Neural Network, English Teaching Assessment, Teaching Evaluation

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## 1. Introduction

In recent decades, neural network studies have rapidly emerged as a multidisciplinary frontier field. Its objective lies in deepening the understanding of the neural mechanisms of human language and its features during use. Many linguists strive to reveal the nature of language formation and development, starting from brain neurons' structure and operational laws. Although we cannot fully comprehend the operating mechanism of language at present, technological progress allows us to continue our understanding through language study [1]. Evaluating the effectiveness of English teaching has become an important topic in tertiary education assessment. Teachers can understand the real-time teaching situation through evaluation results and promptly adjust teaching plans and progress. School management can also measure English teachers' comprehensive teaching ability through evaluation results and adopt scientific and reasonable evaluation models to improve the evaluated object's performance. According to relevant materials, there are many challenges in assessing the effective ness of English teaching. For instance, traditional evaluation methods overly rely on the personal experiences of evaluators, leading to insufficiently fair evaluation results. Therefore, we urgently need a quantitative evaluation method to improve this situation. Their quality is crucial for English classes as it determines a university's success or failure [2]. Many methods to measure classroom effectiveness have unique advantages but are also subjected to many external disturbances. This evaluates English classes more complex and even impossible to express with simple mathematical formulas. By employing neural network technology, we can better assess the level of courses. This technology can assist us in better analysing course content, thereby more accurately predicting course outcomes. This technology can help us better guide our courses, thus promoting course reform more effectively.

## 2. Related Work

From the 1940s onwards, some scientists began to focus on the development of artificial intelligence, with particular interest in the Hebb algorithm. This algorithm, used for training complex connections, facilitated the development of machines capable of deep learning and intelligent decision-making. Over time, some scientists continued to delve into BP neural networks, exploiting their advantages. However, even though they attempted to integrate these with other technologies, due to the presence of usually only one latent layer, their performance and modeling capabilities had certain limitations [3]. In 2006, Tsai first introduced deep belief technology into data processing. Its architecture, composed of many latent layers, significantly enhanced data processing efficiency and exhibited excellent modeling capability [4]. In 2007, Alice and other scientists significantly optimized the traditional auto encoder architecture through persistent efforts, developing a more accurate deep autoencoder model [5]. Furthermore, Alice also innovatively developed a sparse autoencoder model with higher precision, contributing significantly to the development of this field. In 2010, Behnood and other Sub-I developed a new autoencoding technique capable of effectively suppressing noise and preventing model inaccuracies by arbitrarily increasing or decreasing lost information [6]. In addition, Yan and other Sub utilized a tree-structured long short-term memory neural network for emotion recognition. However, in recent years, deep neural network technology has made substantial progress [7] and garnered increasing attention, especially in education. Its usage is becoming more prevalent and increasingly valued, especially for improving teacher classroom performance; it is more convenient and better meets practical needs. Countries like the UK, the US, and Japan have made significant progress in evaluating education quality. They have introduced many new concepts, such as multiple intelligences, constructivism, and Taylor's evaluation model. They have also established a scoring system based on a five-point scale, with George Fisher from the UK pioneering this system. Edward L. Thorndike's book "Introduction to Psychological and Social Measurement" significantly advanced the standardization of education measurement in the United States and Russia, leading to significant breakthroughs in this field. It has also gained widespread application internationally, including national, school-level, social, public participatory, and autonomous evaluations. Most education quality evaluation criteria are based on teacher attitudes, course content, and course implementation [8]. This information is quantified and used to construct various evaluation tools. Commonly used evaluation tools include the analytic hierarchy process, multivariate statistical analysis, fuzzy comprehensive evaluation, fuzzy hierarchy analysis, association analysis, ID3 algorithm, support vector machine, and the BP neural network model [9]. The education quality evaluation model constructed by JuanD W using BP neural network technology achieved satisfactory results. It effectively reduced the cumbersome steps of evaluation and overcame the limitations of the traditional analytic hierarchy process, reflecting the actual situation more accurately. Ge Chun utilized genetic algorithms and BP neural networks to construct a series of weights and thresholds to determine the optimal model, significantly improving classroom teaching effectiveness. In recent years, with the advancement of technology, more and more people are exploring new and more effective ways to measure students' English proficiency [10]. For example, Jufang and Wang Hongyan have both proposed a new, more targeted, operable, reliable, comparable, sustainable, and actionable way to measure students' English proficiency.

# 3. Neural Network Algorithm

## 3.1 The Development of Artificial Intelligence Technology Has Transcended the Scope of Artificial Neural Networks

When *xi(t)* points to *t*, neuron j will obtain data from neuron *i*. When *yj(t)* points to *t*, neuron *j* will produce the corresponding result. Therefore, the shape of neuron j can be described by the following formula:

$$y_j(t) = f\left\{\left[\sum_{i=1}^{n} w_{ij}\, x_i(t) + b_j\right]\right\} \tag{1}$$

*f(•)* represents an activation function, *wij* refers to the weights of the interactions between neurons, and *bj* refers to the minimum requirements of neuron *j*. This is the expression proposed in this article. This article elaborates on all aspects of the neuron model [11,12].

## 3.2 The Concept of BP Neural Network and Network Structure

Many algorithms in deep learning can be implemented using different methods. For example, some common algorithms can learn more efficiently by using dynamic and non-linear weights. These algorithms can help us better understand and predict complex information [13-15]. The autoencoder can convert complex signals into reliable ones through the BP algorithm. Its three-layer structure can effectively suppress noise in the signal, and by adjusting the authority and threshold of the layers, effective signal conversion can be achieved, thereby achieving the purpose of converting complex signals into reliable signals. In this system, we need to use adaptive control techniques to optimize the propagation of digital signals. These techniques include reducing the complexity and reliability of digital signals to a controllable level and using error functions to optimize the propagation of digital signals. In this way, we can effectively extract and propagate digital signals, and use them for production and analysis. The autoencoder converts input information into an intermediate hidden layer, while the decoder converts information into an output layer.

$$h = f(x_i) = S_f\left(W_f x_i + b_i\right) \tag{2}$$

$$y = g(h_j) = S_g\left(W_g h_j + b_j\right) \tag{3}$$

In this statement, *f* and *g* are functions used to encode and decode signals, while *Sf* and *Sg* are nonlinear functions used to activate these signals. Additionally, *Wf* and *Wg*, *bi* and *bj* are matrices used to describe the network's weight matrix and threshold matrix.

Hinton's Restricted Boltzmann Machine (RBM) model greatly simplifies the traditional Boltzmann Machine, as it only considers interactions between the visible and hidden layers, without involving cross-layer unit interactions, thereby making the overall modeling simpler and more efficient [16, 17]. It is assumed that the visible layer unit *v* of the RBM model can follow any exponential distribution, and it can be represented as a bipartite graph model, with *vi* ∈ {0, and *hj* can be represented as (*19581* = 1, 3), ....*m*;. j =1, 2, 3,..... We must know ={*wij, ai,* *bj*} to determine a restricted Boltzmann machine model. Here, *wij* represents the degree of interaction between an object in two different entities, while ai represents the degree of interaction between an object in two different entities. When we consider a set of special cases (*v,h*), our energy formula is as follows:

$$E(v,h|\ \theta) = -\sum_{i=1}^{n} a_i v_i - \sum_{j=1}^{m} b_j h_j - \sum_{i=1}^{n}\sum_{j=1}^{m} v_i w_{ij} h_j \qquad (4)$$

By exponentiating and normalizing the energy function, we find that when both observable or latent hierarchical structures are under specific conditions, their joint probability distribution of (*v,h*) is shown in Figure (5).

$$P(v,h|\ \theta) = \frac{e^{-E(v,h|\ \theta)}}{Z(\theta)}, \quad Z(\theta) = \sum_{v,h} e^{-E(v,h|\ \theta)} \qquad (5)$$

In the case of (θ) acting as a normalization parameter, we can calculate the boundary values of the display layer and the latent layer by applying formula (5). The Deep Belief Neural Network model, invented by Hinton in 2006, is based on Bayesian probability [18-20]. It uses a combination of finite Bosonic filters and adopts a greedy learning method to estimate probabilities effectively.

# 4. Experiment Design and Result Analysis

## 4.1 Experimental Data

In this study, we used information from multiple sources, including information from the Department of Education in the UK and expert feedback. We normalized this information for preprocessing to provide effective model references. We divided the network architecture of this model into three layers, with a target accuracy of 0.001 and learning efficiency of 0.01, and it can undergo up to 5000 training iterations. We also used a single S-shaped responder. Starting from the 2010 level, we collected 1372 samples for training the model, and collected 191 samples at the 2016 level for testing the model. We improved the number of hidden layer neurons in the model, the adaptive learning rate, and the momentum term through carefully designed algorithms to achieve better results. By using actual measurements to check the accuracy of predictions, we can measure the effectiveness of the algorithms through the mean square error (MSE), prediction accuracy, training duration, and iteration frequency, thus gaining a better understanding of their strengths and weaknesses.

## 4.2 Analysis of Experimental Results

By varying three different learning rates in the ranges of (1, 1.3] and [0.5, 1), we constructed a neural network with 15 hidden layers, adopting a training method based on adaptive learning rate changes and a momentum change of 0.85, to ensure that the model could reach the desired results swiftly. Upon analyzing the training dataset, we found a relationship between the given training reference values and actual application reference values. This relationship was evident through our analysis of the Mean Square Error (MSE) and prediction accuracy, as depicted in Figure 1. The chart illustrates that as the learning rate increases, the MSE and prediction accuracy also improve significantly when the rate is increased to 1.2 and decreased to the level of 0.85. At this point, this improvement effect becomes more apparent.

To further test the neural network algorithm's application effects, we implemented it in three ways in English classroom teaching. In this comparison, we selected the Particle Swarm Algorithm and optimized the BP neural network higher education quality evaluation model, as well as the classification weighted grey target decision-making method, to conduct a comparative experiment on the effectiveness of college English classroom teaching. We used these three methods to process 10 sets of data, conducted 20 experiments and recorded the time spent using these methods during the experiments (experiment duration) before calculating the average. The comparison of the experiment durations for the three methods can be seen in Figures 2 and 3.

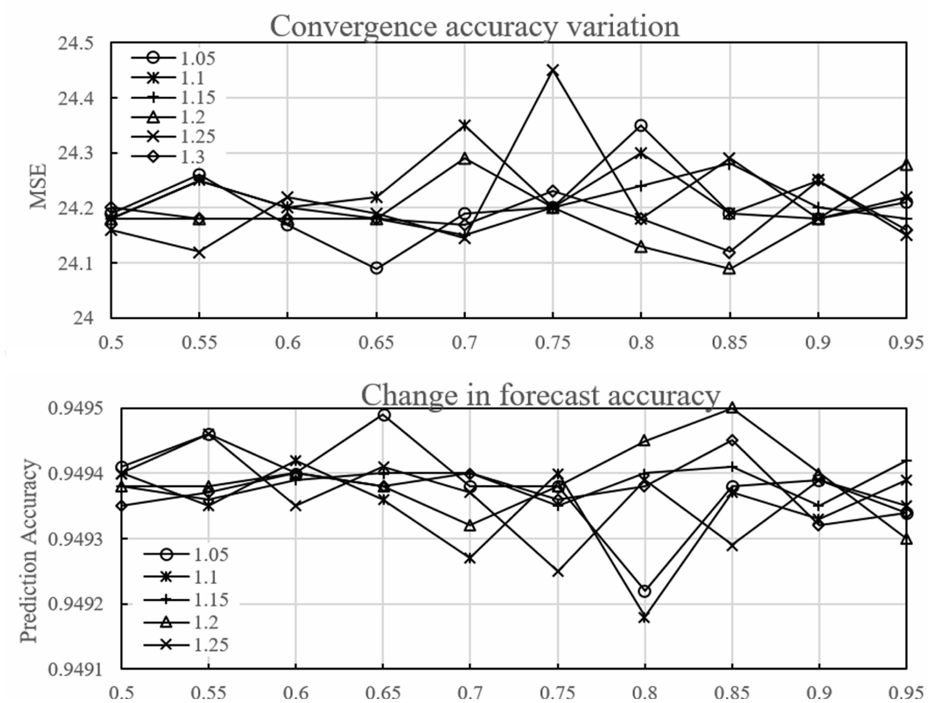


Figure 1. Relationship between the rise and fall of the adaptive learning rate

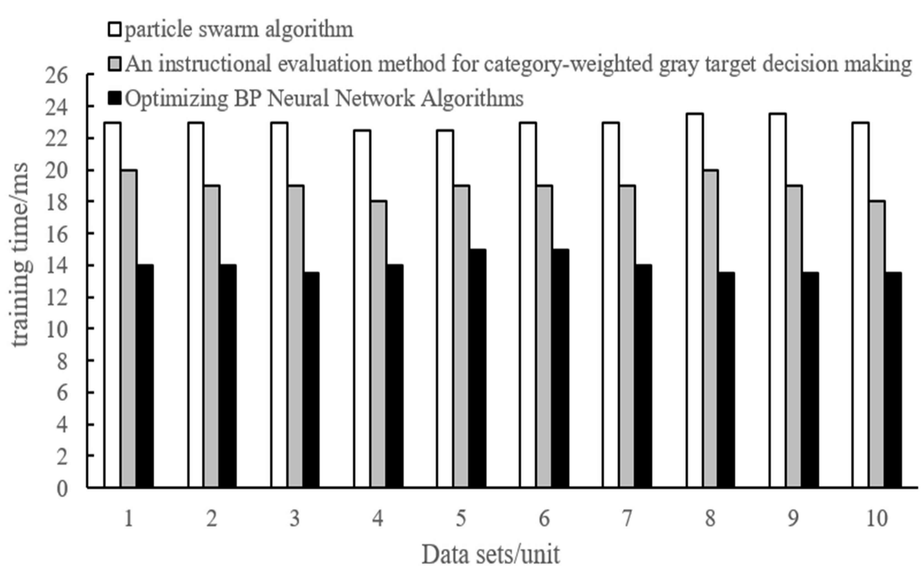


Figure 2. Comparison of training time

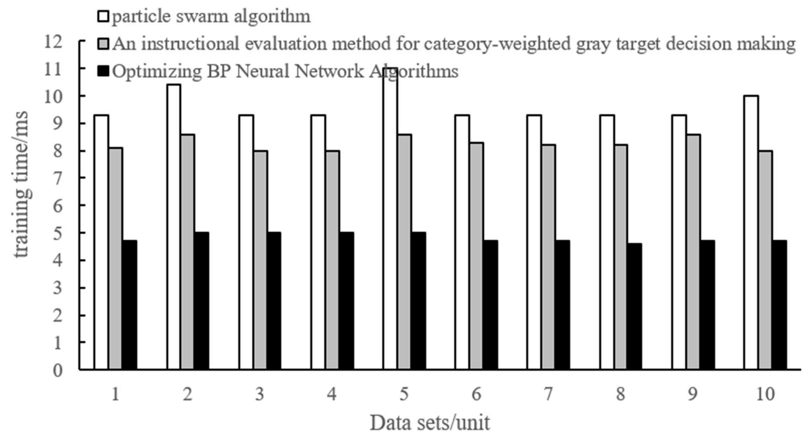


Figure 3. Comparison Results of Test Times

From the comparison results of Figure 2 and Figure 3, it can be seen that the optimal BP neural network algorithm has significant advantages over the other two methods in terms of time efficiency. This grammar uses the shortest training and experimental time, with the training time reduced to 13ms and the experimental time reduced to 5ms. Compared with the particle swarm optimization algorithm, the higher education quality evaluation model method saves 9ms in training time and 4ms in experimental time; The educational evaluation method of category-weighted grey target decision-making saves 3ms in training time and 4ms in experimental time.

# 5. Conclusions

The complexity of the quantitative nonlinear function relationship between the effectiveness of college English teaching and various assessment indicators leads to subjective evaluation scores, affecting the assessment's objectivity and fairness. The paper takes the process of evaluating the teaching quality of vocational college teachers as a system, and examines the teaching quality of universities from the perspectives of system input, output, informatization, and comparison. Computer technology and mathematical methods are simultaneously used to examine the teaching quality of vocational colleges. To accurately evaluate the impact on the effectiveness of college English teaching and comprehensively improve the performance of college English teaching, this paper develops a college English teaching effectiveness evaluation model based on optimized neural network algorithms. The experimental results show that this method has the best evaluation accuracy, a short evaluation cycle, and the best evaluation effect, which has important practical significance in improving the performance of college English teaching. At the same time, it also shows that it is of practical relevance to use the optimized BP neural Network theory to evaluate the teaching quality of college teachers.

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